COST-EFFECTIVE HEALTHCARE TELEMONITORING

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Abstract

The importance of home healthcare telemonitoring for elderly and outpatients has been widely recognised. However, the adoption rate of home healthcare telemonitoring remains low due to limited evidence for cost-effectiveness. The core objective of this work is the cost-effective design of a real-time home healthcare telemonitoring system based on mobile cloud computing. A second objective is to develop a simulation environment in order for us to produce robust evidence for the cost-effectiveness of a telemonitoring system in order to explore technology choices prior to moving to full-scale trials. We are at an early stage, yet the results so far have been encouraging. Whilst we may not be able to deliver a complete solution, we are confident that the methodological contribution of test environment plus simulation models will enable us to put the evaluation of telehealth solutions prior to moving to full-scale trials on a more scientific basis.

Keywords

cost-effectiveness, cost-effectiveness analysis, healthcare, telemonitoring, vital sign monitoring, fall detection, smart home, internet of things, mobile cloud computing, arduino, bluetooth

Introduction

The rise in both ageing and chronic disease populations has become a global issue which calls for a top policy priority to provide proper access to quality healthcare. Though information and communications technologies (ICTs) have been used in almost all aspects of our life, there remains a considerable question of low adoption rate of remote healthcare technologies. One of the main reasons, as indicated by a number of studies [1-2], is a lack of robust evidence for cost-effectiveness. For example, although the reported results of the 2008 UK based Whole System Demonstrator randomised trial were positive, two subsequent studies [3-4] threw doubt on the impact of the intervention.

To address this issue, we set up as our core objective the cost-effective design of a real-time home healthcare telemonitoring system based on mobile cloud computing. Our hypothesis is that the increasing availability of commodity sensor technology and computation resource, such as cloud computing and smartphone, can dramatically reduce the infrastructure costs of telemonitoring. In addition, the usability of the technology is making significant advances - especially in terms of minimising intrusion on the patients‘ lifestyle.

Our second objective is to develop a simulation environment in order for us to produce robust evidence for the cost-effectiveness of a telemonitoring system in order to explore technology choices prior to moving to full-scale trials. Accordingly, a framework based on data from simulated trials and literature review for conducting comparative cost-effectiveness analysis is also proposed.

The remainder of this paper is organised as follows. In next section, we briefly describe the concept and problems of cost-effectiveness of healthcare technologies. Then we focus our discussion mainly on the design and experimental results of our prototype system on the client side mobile platform and sensors. Finally, we conclude with suggestions for future work.

Cost-effectiveness of Healthcare Technologies

The Concept

The increasing demand for better healthcare is manifested in the need to provide better evidence for informed decision making through economic evaluation. In this context, Evidence-based Medicine (EBM), Health Technology Assessment (HTA) and Comparative Effectiveness Research (CER) have been used in many organisations to evaluate the benefits and harms of alternative treatments, technologies or healthcare deliveries. Among all techniques of economic evaluations in healthcare, Cost-effectiveness Analysis (CEA) is widely adopted.

The National Institute for Health and Clinical Excellence (NICE) in the UK [5] defines cost effectiveness analysis as: "an economic study design in which consequences of different interventions are measured using a single outcome, usually in 'natural' units (for example, life-years gained, deaths avoided, heart attacks avoided or cases detected). Alternative interventions are then compared in terms of cost per unit of effectiveness."

Figure 1 represents the concept that there are changes in the health status, associated costs and resulting quality of life and life expectancy of an observed group of patients having received an intervention for a period of time.

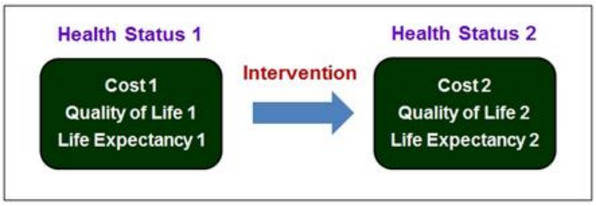

Fig. 1: Components of a cost-effectiveness analysis [6].

For independent interventions, the cost-effectiveness ratio (CER) is calculated to estimate the effects of different interventions by dividing the costs (C) of each intervention by its health effects (E) produced, e.g. life-years gained (LYG) or quality adjusted life years (QALYs):

$$CER = \frac{C}{E} \tag{1}$$

For mutually exclusive interventions, the incremental cost-effectiveness ratio (ICER) is calculated by dividing the difference in costs (ΔC) by the difference in health effects (ΔE) between two interventions:

$$ICER = \frac{\Delta C}{\Delta E} \tag{2}$$

The Problem

A 2006 systematic review [7] classified 578 articles during 1990-2003 from the Medline database as being relevant to the targeted research field of home telehealth. Two of the conclusions drawn by this review were that the impact on those designs for special user groups, such as elderly, needs to be further explored, and that in general, evaluation studies are rare and further research is critical to determine the impacts, benefits and limitations of potential solutions

Another 2007 systematic review [8] included 98 randomised trials and observational studies available as of January 2006 in 17 electronic databases in its review. The key findings were that cost-effectiveness of these interventions was less certain, and that there was insufficient evidence of the effects of home safety and security alert systems.

Then a 2010 systematic review of economic evaluations [9] found only 33 articles that measured both costs and non-resource consequences of using telemedicine in direct patient care. However, the review regarded this as a considerable increase. It concluded that the effectiveness measures were more consistent and well reported than the costings, and that most studies lacked information about the perspective and costing method.

Research Designs

System Design

To better understand the implications of recent technological advances, such as sensor technologies, smart home, Internet of Things (IoTs) and mobile cloud computing, in support of cost-effective telemonitoring, we have conducted a broad review of literature in related fields. Eventually, we decided to develop our system based on mobile cloud computing in order to achieve better mobility, lower intrusiveness, enhance usability and deployability for patients, and lower costs on system setup and operations, among other considerations.

Three key functional components of our proposed system are vital sign monitoring, safety monitoring (primarily for fall detection) and activity monitoring (mainly on movement pattern monitoring). The high-level system architecture consists of four main modules, i.e. User Agent(s), Sensor Nodes, Service Gateway (Cloud Broker) and Public Cloud(s).

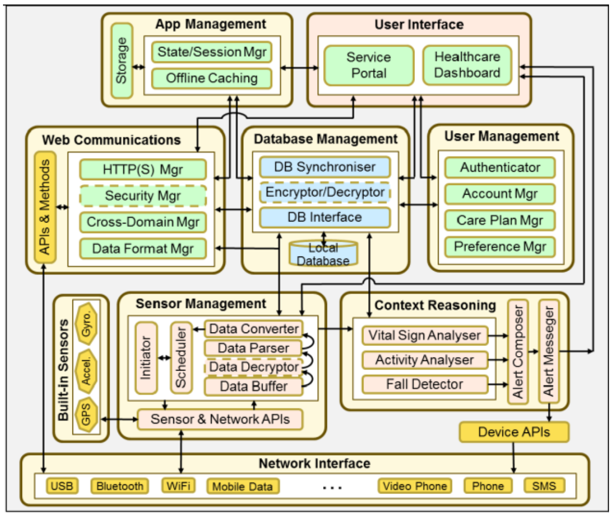

Fig. 2: Architecture diagram of the User Agent Module.

The main functions of the User Agent Module (Figure 2) include: (i) user interface for users to manage the sensors, to set their preferences and care plans for healthcare monitoring and to manage context and health data; (ii) an intelligent data aggregator that connects with a variety of sensors, collects real-time sensor data and transmits it to cloud storage, and performs context/health data reasoning based on preset parameters to automatically trigger an alert; and (iii) a portable personal healthcare assistant that can work with, and without an Internet connection.

The implementation of the User Agent Module is based on Objective-C in iOS 6.1. As for fall detection, we currently adopt a wearable device approach, mainly based on accelerometry-related parameters, such as the sum vector (SV) of acceleration in X-Y-Z axes (see Equation 3). For activity monitoring, we plan to use received signal strength from three triangular deployed reference sensors for in-home location and movement estimation.

$$SV = \sqrt{x^2 + y^2 + z^2} \tag{3}$$

The Sensor Node Module consists of a number of different sensors to collect context data or detect certain events relevant to the monitoring. Currently we use an Arduino-compatible platform (Seeeduino Stalker v2.1 shield manufactured by Seeed Studio) and clinically uncertified sensors (e-Health Sensor Platform v1.0 with optional sensor kits, such as pulse, oxygen in blood, body temperature and body position sensors by Cooking Hacks) for vital sign monitoring.

As for safety and activity monitoring, we use Bluetooth Low Energy (BLE) technology enabled sensors (SensorTag by Texas Instruments with six onboard sensors, such as accelerometer, gyroscope and thermometer). We also use iPhone's built-in sensors, including accelerometer, gyroscope and GPS (global positioning system) sensors, to provide comparative data for fall detection and user location information.

For the purpose of this paper, the other two modules of our proposed system will not be discussed here.

Cost-effectiveness Analysis Framework

Due to limited resources, this research calculates neither CER nor ICER directly, but performs simulated trials to predict the effectiveness of the proposed system and then conduct cost-effectiveness analysis based on a revised comparative effectiveness analysis approach (see Figure 3).

Using this approach, we will compare our simulated trials with existing randomised controlled trials. Data about the costs and effects (the resulting changes in a group of patients' health status from Health Status X to Health Status Y) of a known Intervention Y is first obtained from literature review. Then we can claim that our proposed Intervention Z can provide the same QALY effects or better QALY effects (i.e. Health Status Y+ with Quality of Life Y+ and Life Expectancy Y+) than Intervention Y, if Intervention Z has the same or better functionality/performance. Finally, Cost Z and ICER of Intervention Z are calculated for cost-effectiveness analysis.

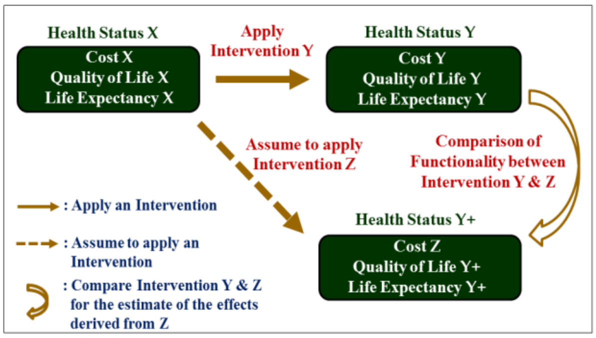

Fig. 3: Concept Diagram for a Comparative Effectiveness Analysis Approach.

Preliminary Results

When building our fall detection algorithm, we first assumed that a fall followed by lying motionless is an emergency that needs to trigger an alert. 30 simulated activities of daily living (ADL), each followed by an intentional forward fall on a cushion, were performed by locating either a Sensor Tag or an iPhone at different places of a volunteer's body, such as ear side, jacket pocket, shirt chest pocket, pants pocket, or handheld. To make our simulated falls closer to reality, we did not strictly confine the sensors to a certain tilting angle or orientation. Such a research design is apparently different from a number of studies [10-12].

The results from 22 falls (eight falls were excluded due to noisy data) revealed that when SV first drops below 0.79g (1^{st} threshold) before bouncing over 1.48g (2^{nd} threshold) and then after a few oscillations it remains in the interval between 1.125g and 0.89g (3^{rd} threshold) for more than 2 seconds, a serious fall might have occurred. Nevertheless, dropping or throwing an accelerometer could produce similar SV signature. Consequently, we add another threshold at 0.15g (4^{th} threshold) to detect a free fall situation, which enables us to distinguish all device drops/throws from human falls.

Tab. 1: Results of fall detection using 3-threshold or 4-threshold algorithms. (accelerometer range: ±2g, sampling rate: 10Hz)

	3 thresholds	4 thresholds
Sensitivity	95.5%	95.5%
Specificity for device drops/throws	0%	100%
Specificity for ADLs	95.5%	95.5%

In Table 1, sensitivity is defined as the percentage of successfully identified falls and specificity is the percentage of successfully identified non-fall tests. Indeed, we have also developed another algorithm to identify intentional device shaking events, which sometimes can produce almost identical SV signatures to human falls. However, instead of using the new algorithm at the expense of less sensitivity, we add a function to ask for user confirmation before an alert is sent to remote carers.

Regarding vital sign monitoring, the accuracy and reliability of the used sensors have been disappointing so far. For example, the highest body temperature measured by the e-Health Sensor Platform's thermometer was under 30 degree celsius and the body position sensor just did not work. According to the manufacturer of the e-Health Sensor Platform, a possible reason might be incompatibility between the e-Health Platform and the Seeeduino Stalker shield, as the former is designed for Arduino. However, after some relatively minor modifications to the sensors and wiring, our User Agent Module can start receiving meaningful data from some of the sensors. We believe the results can be further improved with more work.

As for movement pattern monitoring, due to limited resources, we currently have only one SensorTag. By measuring received signal strength from a man-carried SensorTag, we can roughly estimate the distance between the man and the User Agent with an accuracy of around two to three meters.

Discussion

We are at an early stage, yet the results so far have been encouraging. To enable ourselves to satisfactorily conduct cost-effectiveness analysis and to make claims about the generalisability of this research, we first need to further improve the reliability and accuracy of our event reasoning algorithms, as well as the sensors. The technical problem of imcompatibility among devices also needs to be better resolved. Meanwhile, a more stable and well-defined testing environment has to be carefully designed to make our simulation more meaningful and robust.

Conclusion

In this paper, we have discussed the long-standing problem of lacking robust evidence for cost-effectiveness of healthcare technologies. To tackle this issue, we have proposed a home healthcare telemonitoring system architecture based on mobile cloud computing and developed a proof-of-concept prototype together with a comparative cost-effectiveness analysis approach based on simulated trials. Through the experimental work, we believe that the proposed system is a good foundation for moving forward.

In addition to the future work mentioned in the Discussion section, we will also work on the development of the Service Gateway and Cloud Modules to integrate all the proposed system components as a whole, and complete simulated trials and cost-effectiveness analysis. Whilst we may not be able to deliver a complete solution, we are confident that the methodological contribution of test environment plus simulation models will enable us to put the evaluation of telehealth solutions prior to moving to full-scale trials on a more scientific basis.

Acknowledgement

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